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Diffusion Dynamics of Radiology IT – Systems in German Hospitals – A Bayesian Bass Model

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Abstract. Radiology has a reputation for having a high affinity to innovation – particularly with regard to information technologies. Designed for supporting the peculiarities of radiological diagnostic workflows, Radiology Information Systems (RIS) and Picture Archiving and Communication Systems (PACS) developed into widely used information systems in hospitals and form the basis for advancing the field towards automated image diagnostics. RIS and PACS can thus serve as meaningful indicators of how quickly IT innovations diffuse in secondary care settings – an issue that requires increased attention in research and health policy in the light of increasingly fast innovation cycles. We therefore conducted a retrospective longitudinal observational study to research the diffusion dynamics of RIS and PACS in German hospitals between 2005 and 2017. Based upon data points collected within the "IT Report Healthcare" and building on Rogers' Diffusion of Innovation (DOI) theory, we applied a novel methodological technique by fitting Bayesian Bass Diffusion Models on past adoption rates. The Bass models showed acceptable goodness of fit to the data and the results indicated similar growth rates of RIS and PACS implementations and suggest that market saturation is almost reached. Adoption rates of PACS showed a slightly higher coefficient of imitation ($q = 0.25$) compared to RIS ($q = 0.11$). However, the diffusion process expands over approximately two decades for both systems which points at the need for further research into how innovation diffusion can be accelerated effectively. Furthermore, the Bayesian approach to Bass modelling showed to have several advantages over the classical frequentists approaches and should encourage adoption and diffusion research to adapt similar techniques.

Keywords. Bayesian Data Analysis, Bass Diffusion Model, Hospital Information Technology, Diffusion of Innovation, RIS, PACS

1. Introduction

Radiology is often regarded as one of the most IT-savvy and innovation-friendly medical domains [1,2]. Accordingly, Radiology Information Systems (RIS) and Picture Archiving and Communication Systems (PACS) are widely established information technologies in health care that were among the first electronic systems introduced and utilized in primary and secondary care settings alike [3]. Radiology departments in hospitals have specific requirements with regard to data and image processing as well

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as workflow management that are not well met by the general, less department-specific components of the hospital information systems (HIS) which explains why radiology departments started to develop and use their own specific systems in the first place [4]. While a RIS manages radiological patient information, e.g. scheduling and examination as well as administrative tasks (e.g. billing), a PACS processes, stores, queries and displays radiological images and ensures information exchange between radiological modalities and services.
Furthermore, in light of recent technological advances in automated image processing and interpretation, radiology as a whole is expected to witness profound disruptions with regard to AI supported diagnostics and decision-making tools that start to outperform human capabilities and are built upon or are integrated in RIS and PACS [5].
In order to forecast future developments and to gain better understanding of the diffusion dynamics of health information technologies (HIT) in general, the methodological imperative has to be to conduct longitudinal research and to apply appropriate techniques that model past developments. In HIT adoption and diffusion research, Rogers' Diffusion of Innovation (DOI) theory is among the most referenced frameworks [6]. Yet, when researching diffusion dynamics at the population level, a meaningful application of DOI should be carried out in conjunction with its mathematical specification, Frank Bass' diffusion model [7,8]. This model proposes a widely accepted fit-function to model the diffusion of innovation over a given timeframe that has been used for HIT diffusion in selected studies throughout several different care settings [9–11].

In this study, we combine a Bayesian approach with the Bass model. Typically, Bass models are fitted using traditional statistical methods, such as Non-Linear Least Squares [12], while Bayesian analysis has fundamental advantages: Briefly, in Bayesian analysis a (multidimensional) space of candidate model parameters is explored and credibility is reallocated towards values that are most plausible in the light of the data. As a result, complete probability distributions of the parameters and predictions are available. Yet, Bayesian models require higher computing power which, however, is not problematic anymore in most use cases today. In conclusion, these methodological improvements are desirable in order to obtain models with richer information as Hassan and Blandon demonstrated in 2016 [13].

The goal of our study is twofold: First, we aim to investigate current adoption rates as well as the past course of developments in the adoption rates of RIS as well as PACS in German hospitals as a means of gaining a better understanding the diffusion dynamics of health IT innovations. Second, we aim to utilize our data in order to showcase a Bayesian approach to fit Bass diffusion models with the intention to promote advanced methodologic approaches in HIT adoption and diffusion research.

2. Methods

2.1. Data Sources

We utilized the data of the IT Report Healthcare, an independent research initiative that investigates digitalization of German hospitals by surveying Chief Information Officers on a voluntary basis through regular cross-sectional surveys. Since 2002 multiple surveys have been conducted in 2005, 2007, 2009, 2011, 2013, and 2017 that offer information about the implementation of radiology systems RIS and PACS in a consistent manner. We merged the independent survey data into one dataset which represents the development of a 12-year time period [14]. Additionally, the consolidated dataset contains demographic information (bed count and type of ownership) throughout all years and of each participating hospital. We post-stratified our data based on the federal hospital index, the "Krankenhausverzeichnis", using both demographic variables to mitigate a potential selection bias as those two factors are known to confound with the degree of IT-maturity [15].

2.2. Bayesian Bass Model

Initially, based on the post-stratified dataset, we calculated the cumulative proportion of adopters for each system and each available year to graphically illustrate the adoption curve on a timeline. Next, we fitted a Bass diffusion model (Eq. 1) to investigate diffusion dynamics described by two parameters, p and q, which represent the influence of innovators and imitators respectively [7].

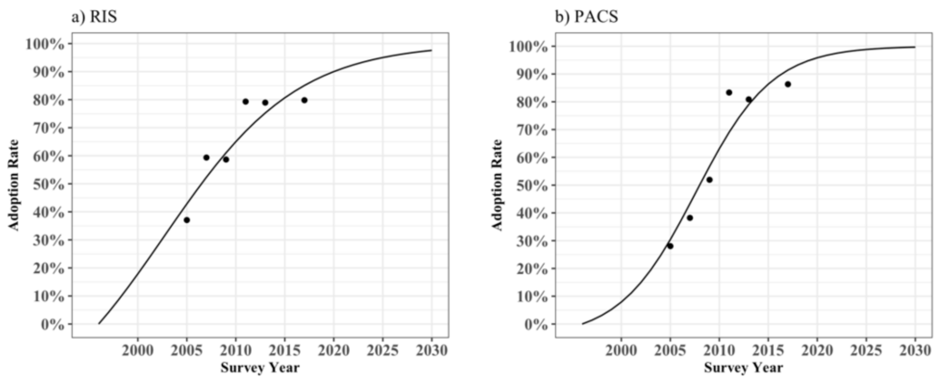
$$F(t)=\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} \tag{1}$$

In contrast to other studies, which rely on traditional fitting procedures such as non-linear least squares, we developed a Bayesian approach to estimate coefficients of the Bass model denoted as $\phi(p,q)$. Basically, this approach tries to find the most likely bivariate parameter combination of p and q given the actual observed data $P(\phi(p,q)|\text{Data})$. As described in the introduction, the Bayesian approach offers advantages such as estimating the complete bivariate probability distribution of the model coefficients. Additionally, the Bayesian model is able to incorporate prior knowledge about the coefficients.

Four elements compose a Bayesian model: First, the data structure, second, the knowledge about the model parameters prior to the analysis, third, the likelihood function and fourth, the computational method to calculate the model parameter. We describe all four elements of our Bayesian Bass model in the following section.

First, in the context of diffusion research, we used a time series design with six distinct points in time and 1163 single data points as our data basis. Rather than processing the aggregated adoption rates of each single time point as in traditional methods, each data point is processed during the model computation. Second, we choose rather unspecific prior distributions of both model parameters p and q. We assumed them to follow a normal distribution centered at zero with a relatively large standard deviation of 0.6, spanning a vast range of possible and plausible Bass model parameters [16]. This configuration can be assumed as a noncommittal prior, because we do not make any specific assumptions of p and q prior to the analysis. Third, the likelihood function of the Bayesian Bass model describes the adoption status of each participating hospital, denoted as y_i, with a Bernoulli distribution with parameter μ_i. This parameter is derived from the Bass formula (Eq. 1). Generally, the likelihood function computes the probability of the data under a specific set of parameters (p and q). Fourth, the Markov Chain Monte Carlo (MCMC) simulation was utilized to estimate model coefficients through the open source software *rjags* [17] which is freely available for the statistical programming language R. We used 500,000 MCMC iterations with a thinning of 50 iterations to control for autocorrelation. The burn-it period was 5000 iterations. We used R throughout all steps of analysis, i.e. preprocessing, data merging, post-stratification and modelling. Furthermore, we developed an open source R package that extends the functionality of R to fit, summarize and plot Bayesian Bass models as described in this section (available at jnshsrs.github.io/bayesianbass).

Figure 1. Diffusion curves a) RIS and b) PACS



3. Results

Time points from six distinct cross-sectional studies, conducted between 2005 and 2017, with a total of 1163 data points were consolidated for longitudinal timeline analysis. The average sample size of the surveys was 194, ranging from 104 to 323 hospitals with an average bed count of 389 beds per hospital throughout all years. Hospitals of all types of ownership participated in the surveys. However, we post-stratified our analysis using type of ownership and bed count as adjusting variables to avoid possible self-selection bias since both variables are likely to be linked to survey participation and the degree of digitalization.

Table 1. Hospital demographics and adjusted adoption rates

Year	Adoption RIS	Adoption PACS	Average Bed Count (Sample)	Proportion Private Ownership (Sample)	Sample Size (n=1163)
2005	37.1%	28.0%	315.71	16.4%	323
2007	59.3%	38.2%	398.98	11.4%	123
2009	58.7%	51.9%	342.79	27.9%	104
2011	79.3%	83.3%	459.82	17.8%	163
2013	78.9%	80.9%	406.81	21.7%	235
2017	79.8%	86.3%	493.02	16.7%	215

We fitted two distinct Bass models on the adoption rates of PACS and RIS respectively. MCMC simulation diagnostics for both models revealed converged chains and no conspicuous autocorrelation. Therefore, we assumed model coefficient estimates to be representative. The $\chi 2$ goodness of fit tests showed that both models described the data well.

Table 2. Bass Model Coefficients for each system with Highest Density Interval (HDI) boundaries. HDI is derived from MCMC samples. Any value within the interval has a higher density than values outside the HDI. The total mass of values inside the HDI is 95%.

	Bass Model		Goodness of Fit		
System	**p (Innovation)**	**q (Imitation)**	**df**	**Statistic**	**p-value**
PACS	0.012 95% HDI [0.008-0.017]	0.246 95% HDI [0.204-0.292]	5	3.698	0.406
RIS	0.040 95% HDI [0.026-0.056]	0.107 95% HDI [0.050-0.159]	5	5.914	0.450

The diffusion curve of both systems show comparable adoption rates throughout the survey years in terms of both having a high initial increase in adoption rates and somewhat stalling growth rates in later years. However, diffusion of RIS had a quicker uptake compared to PACS. This trend is represented by a higher Bass model coefficient of innovation p (p_{RIS} = 0.04, p_{PACS}=0.012). In contrast, the PACS imitation effect is approximately twice as large as the RIS one. This suggests that the adoption process of PACS is mainly driven by hospitals 'mimicking' their peers who already adopted the system (q_{RIS}= 0.107, q_{PACS}=0.246). Basically, a high coefficient of imitation indicates lower rates in the beginning but subsequently accelerating adoption. Furthermore, RIS and PACS will achieve full market saturation according to the model as suggested by the positive coefficient of imitation. As predicted by both Bass Models, in 2020 both systems will likely approach adoption rates of at least 90% in German hospitals as indicated in Figure 1 (RIS = 90.0%, PACS = 95.5%). Figure 2 provides the complete probability distribution of the estimated adoption rates for both systems in 2020.

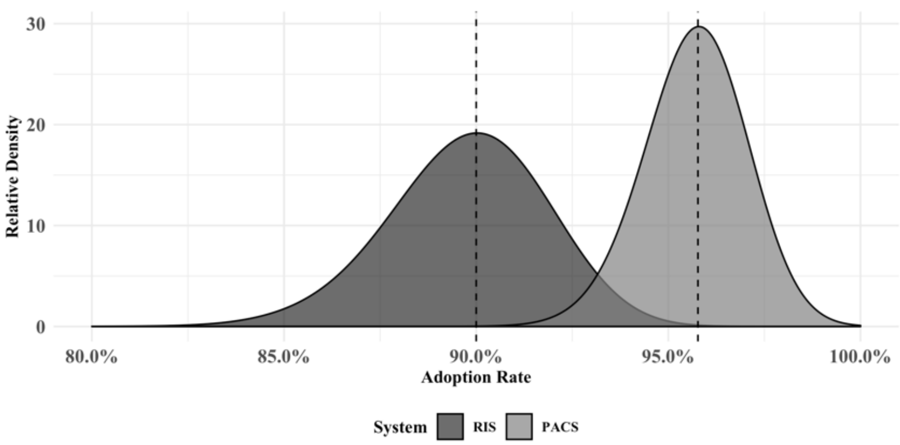


Figure 2. Prediction of hospital adoption rates for RIS (90.0%) and PACS (95.5%) in 2020. The Bayesian Bass model provides a complete distribution of the predicted adoption rates. Vertical dashed lines represent the average estimated adoption rate. The wider tails of the probability distribution of RIS adoption indicate a higher uncertainty in the estimate compared to the PACS adoption estimate.

4. Discussion

We investigated the diffusion dynamics of radiologic systems in German hospitals. This study offers insights into the adoption process of important and widely used electronic information systems in hospital's RIS and PACS. Furthermore, this is one of the first studies combining the Bass diffusion model with a Bayesian approach and the first study applying this approach in the field of HIT adoption research.

RIS and PACS show a similar course of development that appears to be relatively parallel. This seems rather unsurprising since both systems complement each other in radiology departments and when integrated, both systems match patient demographics, medical record and images [18,19], leading to more efficient and safe patient care. However, the Bass model did reveal some differences in the diffusion patterns: RIS showed to spread relatively quickly. The Bass model represents this fact with a high coefficient p which indicates the important role of innovators in the adoption process. In contrast, the imitation effect was relatively low for RIS compared to PACS. The quick adoption of RIS slowed down over time and eventually PACS adoption rates surpassed them due to the higher imitation effect (Fig. 2).

The role of imitation as a driver of the uptake in PACS may be associated with different factors. The uptake might be correlated with purchases of state-of-the-art digital medical image devices and the availability of DICOM which facilitates not only the integration of modalities and services within one radiological unit but also the digitalization of the wide-ranging radiological environment of hospitals. Also, the increased availability of faster and higher storage capacities at lower costs is likely to have accelerated their uptake. The imitation effect in the context of PACS and DICOM may furthermore indicate interorganizational health information exchange with other care providers. Although we may not directly infer the existence of DICOM from the availability of PACS (since a digital radiological unit does not necessarily guarantee DICOM [20]), the most recent IT Report Healthcare in 2017 revealed widespread availability of DICOM, as 89.2% of all hospitals reported its use in some way or another [21], which additionally validates our finding.

Some limitations have to be considered in our study: Most importantly, the participation in the surveys has always been on a voluntary basis, which explains the moderate response rate and which might have caused a self-selection bias. Yet, we tried to mitigate this issue by applying post-stratification. We nevertheless might have missed some confounding variables.

Furthermore, when drawing conclusions from our model, we have to take into account that although we processed 1163 data points, we only had six distinct time points at our disposal over a rather long time period of 12 years. The literature showed that when more time points are available, Bass model coefficients might change in that p tends to increase while q decreases [22]. However, our findings are in line with 1.) published Bass models, where typical values for p ranging between 0.01 and 0.03 and typical values for q ranging between 0.1 and 0.3 [8,22] and 2.) with comparable studies in the field of HIT diffusion [9,23].

Longitudinal data is difficult to obtain in independent research initiatives and requires lasting efforts, yet we monitored the diffusion of two radiology systems over a time period of 12 years which provides deeper insights in terms of a more complete picture in comparison to cross-sectional snapshots which are known to be fairly unreliable [24,25]. Looking ahead, it might become more difficult to draw clear lines between systems that have mostly been viewed as being distinct from one another in the past such as RIS and PACS. Modern product designs in health informatics are often based on platform and cloud-based architectures that increasingly blur the boundaries between classic separations. Measurement efforts might thus require a recalibration from looking at "systems" to focusing on more specific and task-based functionalities, such as image based CDSS, drug-allergy alerts, etc.

Bayesian models are able to offer a remedy for the difficulty of obtaining longitudinal timeline data by incorporating prior knowledge about the model coefficients, e.g. from previous diffusion models of similar technologies. This ability enables them to compensate for a weaker data basis as demonstrated by Hassan and Blandon [13]. Therefore, besides providing richer information compared to traditional Bass models, the utilization of a Bayesian approach seems to be a methodological imperative not only for retrospectively researching adoption and diffusion of established systems, but also for forecasting the developments of newer, innovative systems such as clinical decision support systems (CDSS) in image processing which promise to promote safer and better patient care.

In a political field such as health care, forecast models may provide policy makers with valuable information about the adoption process. In this context, Bass models can be utilized to describe the uptake of other electronic systems with respect to the influence of innovators and imitators. Additionally, the models can help to benchmark findings with other countries and contrast differences with respect to national political strategies to identify barriers and facilitators of various eHealth technologies, not only in secondary care settings. Furthermore, the Bayesian approach worked well on our data and the methodological advantages should encourage researchers to make use of this technique.

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